Policy Research Project: Solar Diffusion of Innovations

Low and Middle- Income PV Adoption: Business Models and Policy Correlates

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ABSTRACT

This team's research explored income differences between households that adopt PV through property assessed clean energy (PACE), Solarize and third-party ownership (TPO) and those that adopt PV outside of those programs. The analysis focused on three states: California, Connecticut, and Oregon. The project included a descriptive component, comparing incomes for various customer groups (including Solarize and PACE customers), in addition to econometric modeling to understand whether TPO, Solarize, and PACE programs drove PV deployment into new demographic groups. An important assumption of the analysis was that the income of PV adopting households equates to that of the corresponding census block group.

The team found that TPO systems and PACE-financed PV systems tend to be in lower income areas, indicating that these models have been effective in reaching lower income markets. PV adopters using TPO had average household incomes that were $2,000-$9,000 per year lower than other PV adopters in the three states analyzed. In California, PV adopters using PACE financing had average household incomes that were $8,000 per year lower than other PV households. Perhaps not surprisingly, lower income adopters tended to purchase smaller-sized PV systems than higher-income households.

Solarize programs, on the other hand, tend to correlate with higher income areas, indicating that though Solarize may be effective in reducing installed prices, higher income areas were those benefiting from those lower prices. This does not imply that Solarize is ineffective in lower income areas, but rather that the Solarize programs analyzed in this project may have been specifically targeted toward higher income areas, with an *ex ante* expectation of higher chances of success. Further analysis is needed to assess the effectiveness of Solarize programs in reaching lower income markets, all else equal. The robustness of these results could also be improved by using household-specific income estimates (rather than census income levels at the block group level).

1. INTRODUCTION

Electricity generation through the burning of fossil fuels was the largest single source of carbon dioxide emissions in the United States in 2016 (EPA, 2018). States have implemented various federal and local policies to encourage investments and adoptions of renewable energy technology in order to reduce emissions, to lessen dependence on the foreign energy sources, and to increase job growth in the new clean energy fields. These include, among others, renewable portfolio standards (RPS), net metering, feed-in tariffs (FiT), and multiple financing options and incentives. The SunShot Initiative, launch in 2011 by the Department of Energy, has set a goal of lowering the cost of residential solar photovoltaics (PV) to $0.05 per kilowatt hour by 2030 (Gillingham et al., 2017). Approximately 75% of the total U.S. residentials are comprised of the low or moderate income (LMI) households (Fry and Kochnar, 2016); thus they represent a large untapped market for solar PV installations. High upfront costs have consistently been cited as one of the most prominent barriers to the residential solar PV deployment. Other potential market barriers are the lack of customer awareness, illiquidity of investment, and the uncertainty of the investment payoff (Kirkpatrick et al., 2014).

Government support has lead to the emergence of new business models and creative financing options to address these barriers. Third-party ownership (TPO) and Property Assessed Clean Energy (PACE) are financing options that make it easier for households with low cash flow to pay for solar power. Solarize programs allow residents to benefit from discounted rates through group purchasing. In order to sustain solar PV industry growth and continued cost reductions over time, it is crucial for policymakers to assess the effectiveness of these strategies and to identify important drivers within each program that influence solar penetration to the LMI customer segment.

The primary objective of this study is to investigate whether and to what extent PACE, TPO, and Solarize programs are expanding residential solar PV adoption to the LMI market. In particular, we seek to understand how PACE and Solarize perform at increasing LMI adopters compared to the more established TPO option. Observations that are not flagged as PACE, Solarize, or TPO will form the baseline group in this analysis and the magnitude and size of the program coefficients in the regression analysis will represent program effectiveness. The secondary objective of this study is to identify any significant factors within each program design that influence higher solar intake in LMI customers, which is reflected through the lower average household income. Understanding how LMI households respond to adoption programs is important in order to develop more successful solar expansion strategies. This project also provides a novel quantitative assessment by which policymakers can tailor future approaches to target LMI market segments.

2. BACKGROUND AND RELATED LITERATURE

2.1 Recent Trends

The solar energy market has witnessed quick dramatic growth globally and in the United States. Installed solar PV capacity in the residential sector grew by 51% in 2014 compared to the previous year (Ameli et al., 2017). A significant decrease in the price of PV modules worldwide began in 2009 and led to a period of declining installed prices. Between 2009 and 2013, solar PV system prices fell by 50% (Barbose et al., 2014; Bazilian et al., 2013). Since 2012, module prices have remained relatively steady, but installed prices have continued to trend downwards due to shrinking "soft costs" (Barbose et al., 2016). Over the long-term, installed price declines are a result of drops in both hardware and soft costs including marketing, customer acquisition, installation labor, permitting, and installer profits.

The high initial investment costs required and long payback times resulted in a market saturation of solar adopters with higher annual income (defined as yearly income >80% State AMI) at first. However, starting in 2010, there is a significant incline in the proportion of LMI adopters (40-80% State AMI) (Darghouth et al., 2017). An analysis done by LBNL shows that while a substantial portion of residential PV installations are in moderate-income neighborhoods, adoption trends still skew towards higher income areas (Barbose et al., 2017).

There are several mechanisms driving the rise of the residential solar PV market segment aside from falling system prices. Solar market maturity, as seen in California, results in more homogenous prices across the geography and increased exposure to information channels for potential adopters (Gillingham et al., 2016, Reeves et al., 2017). The availability of different adoption programs like PACE, Solarize, and TPO may also be encouraging solar uptake in less affluent market segments by financing the upfront hardware and installation costs or reducing soft costs (Davidson and Steinbert, 2013; Sigrin and Drury, 2015). While previous literature has established the growing LMI segment in the residential solar PV market, there is little quantitative evidence to show that PACE, Solarize, or TPO is shifting the market towards low or moderate-income adopters.

2.2 Solar Adoption Programs

We introduce the adoption programs analyzed in this project and present the logical causal mechanisms through which they may be extending the solar PV market to LMI customers. While this paper will not provide confirmation of causal mechanisms, we will comment on possible explanations for the observed effects.

Property Assessed Clean Energy (PACE)

PACE program is a long term financing option, in which the upfront cost of solar installation is transformed into a loan that is repaid through property tax assessment (Kirkpatrick and Bennear, 2014). Since 2008, it has financed over 132,000 residential energy efficiency/renewable energy projects, totalling over $3.3B -- $2.85 between 2015-2017 (Wolfe et al., 2017). An assessment of PACE from California shows counties that introduced PACE exhibit faster residential solar expansion than neighboring counties that do not introduce PACE (Ameli et al., 2017) .

The unique characteristic that sets PACE apart from other financing options is that the loan is attached to the property rather than the customer. This lowers the risk of investment for purchasers because the homeowner would not be responsible for the repayment if the property is sold (Wolfe and Lovejoy, 2017). PACE also potentially reduces upfront costs through tax incentives. While financing could open the market to LMI adopters, PACE financing value is determined by the value of home, which tends to be low for LMI households, thus limiting the maximum financing value received. Moreover, there are minimum credit score requirements to apply for PACE program, which also limit the potential LMI customer base (Wolfe and Lovejoy, 2017).

Considering these factors, we expect PACE to be effective in the middle-income segment but ineffective for lower-income adopters. Our hypothesis for PACE is that it will be associated with a ***moderate shift*** *towards lower median income households.* Our analysis of PACE will be limited to California.

Solarize

Solarize is a joint effort between homeowners to expand residential PV adoption in the community by selecting installers with competitive cost-benefits and conducting limited-time programs (Hausman and Condee, 2014). Solarize becomes attractive for residential adopters, particularly LMI population because it decreases total PV installation costs by taking advantage of economies of scale, negotiating installation rates, and implementing a tiered pricing mechanism.

Solarize utilizes the grassroot approach and social (peer) effect in its marketing strategies to bring in groups of customers and achieve lower costs. Since each campaign is specifically tailored to the target community, the resulting adoption rate varies across different solarize jurisdictions. For this study, we will assess Solarize program implementation in Oregon, where Solarize was firstly launched. We will also examine Solarize in Connecticut. The Solar Energy Evolution and Diffusion Studies (SEEDS) program from the Department of Energy (DOE) allowed Connecticut to create several campaign alterations from the regular Solarize program, producing ten different campaigns in 2012-2015. The campaign characteristics are described on Table 1. We hypothesize that we will see a shift towards lower median income households among Solarize adopters compared to TPO, but the ***magnitude of shift will vary*** across localities because of the influence of market advertising and social factors that our data will not capture. Table 1 displays the characteristics of the Solarize designs. Most of the campaigns only vary from the others in one attribute.

Table 1: Solarize campaign characteristics (Gillingham and Bollinger, 2016)

Campaign Design	Program	Start/End Date	Length of program	Town motivation	# of installers	Pricing mechanism
1	Phase 1	9/14/12 - 3/7/13	20	competitive	1	tiered

2	Phase 2	4/1/13 - 9/13/13	20	competitive	1	tiered
3	Phase 3	10/8/13 - 3/10/14	20	competitive	1	tiered
4	Express	12/11/13 -2/21/14	12	competitive	1	tiered
5	Choice	12/10/13 - 4/25/14	20	competitive	3	tiered
6	Phase 4	4/24/14 - 10/7/14	20	competitive	1	tiered
7	Select	4/29/14 - 10/14/14	20	random	1	tiered
8	Prime	11/17/14 - 4/28/15	22	competitive	1	one price
9	Online	11/10/14 - 4/10/15	20	competitive	>5	tiered
10	Phase 5	12/2/14 - 4/22/15	22	competitive	1	tiered

Third Party Ownership (TPO)

TPO has changed the US PV market and expanded solar diffusion across variety of residential market segments with the new financing method that is different from previous customer-owner payment (Nemet et al., 2017). TPO provides solar PV ownership through leasing or power purchase agreement for PV-based electricity in the property (Davidson et al., 2015) TPO systems also offers lower solar installation rate than customer-owned rate in most states analyzed (Barbose & Darghouth, 2016), creating easier access for LMI adopters, thus induced higher share of TPO system amongst LMI population in California, Connecticut and Oregon (Darghouth et. al, 2016). With such a wide acceptance across the spatial boundaries of our project, TPO holds a significant role as a reference when measuring the effectiveness of other adoption programs like PACE and Solarize. For these reasons, we expect TPO to show ***a large shift in lowering the median household income of PV adopters.***

3. DATA

3.1 Data Filtering and Clean-up

This project leveraged the residential PV system installations database provided by Lawrence Berkeley National Lab as part of the annual Tracking the Sun (TTS) dataset. This database corresponds to over 1,000,000 system-level observations within the 1998 - 2016 timeframe, also includes detailed information of system size, installation date, installation jurisdiction (city/county/state), customer segment type, and flags to indicate whether a PV system was financed under a PACE, Solarize, or Third-Party Owned program. Additionally, we also incorporate the U.S. Census and Experian database to estimate the block group median income and the address-level PV adopters income respectively. For the purpose of this study,, we are focusing on the residential solar PV installation for single family with owner-occupied housing.

We segment our data based on the state where adoption program is employed: California, Connecticut, and Oregon. For each datasets, we filter the We select the 2008-2016 timeframe to limit our analysis at the recent installations in which adoption programs have been executed. We choose only residential system installation with system size of 20 kW and below to avoid any commercial / multi-family housing incorporated into the analysis. We also clean the data to only include counties where either PACE or Solarize, TPO, and other solar programs are available because it is more relevant for understanding the adoption program effect in comparison to the broader population.

From here, we select variables that served as either input or as as input and/or output parameters. including the block group median income, system size, solar adoption program (PACE, Solarize, and TPO), State, and County. Additionally, we create some extra variables to refine our analysis, such as LMI flag (Posigen and Grid Alternatives), Solarize campaign, and county-quarter. These treatment has resulted in 591,632 system-level observations and eight predictor variables that are divided into three categories: Binary (PACE, Solarize, TPO, Posigen, and Grid Alternatives), Continuous (system size), and Factor

(Solarize campaign and county-quarter). It is dominated by systems installed in California (95.25%), followed by Connecticut (3.16%) and Oregon (1.59%).

System Count by Adoption Model, per State

State	PACE	TPO	Solarize	Solarize and TPO	Other	Total System Count	% Subsample
CA	10475	221569	0	0	331489	563533	95.251
CT	0	8022	3236	4894	2529	18681	3.158
OR	0	3381	551	72	5414	9418	1.592

Table 2: System-level observations by adoption model for each State.

3.2 System Size Variable

System size is one of the main PV characteristics that affect PV pricing, which is the primary barrier of solar installation in the LMI population (Nemet et al., 2017). We follow previous literature by including a system size variable to capture the strong effect of economies of scale (Nemet et al., 2016). However, following a recent study by LBNL (Darghouth et al., 2017) we expect the LMI adopters to opt for ***smaller size system*** , which is consistent with the home value, house size, and purchasing power of LMI households.

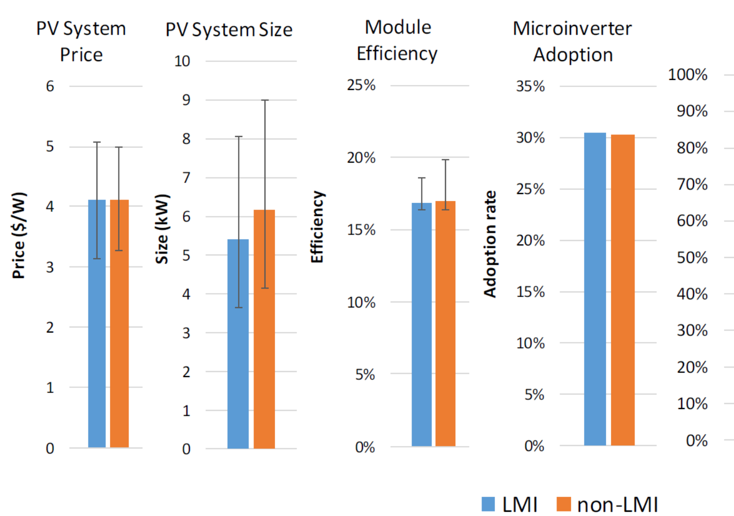

Figure 1: PV system characteristics for LMI and non-LMI adopters (Darghouth et al., 2017).

3.3 LMI-installer flag

In addition to the adoption program and system size, we also introduce LMI-installer flag to control the LMI effect in the market segment where our selected programs are employed. Two different installers in PACE (California) and Solarize (Connecticut/Oregon) jurisdictions have been selected to represent this LMI effect: PosiGen in Connecticut and Grid Alternatives in California. Posigen has partnered with Connecticut Green Bank to launch the Solar for All incentive program (Wadleigh et al., 2017). This program, which targets LMI communities in particular, offers solar leasing without down payment necessary regardless of the credit score ratings. On the other hand, Grid Alternatives (Wadleigh et al., 2017), a California-based non profit organization, administers two LMI-focus solar incentives program to make solar available to the underserved communities, including the Single Family Solar Housing (SASH) and low-income Solar Demonstration Project.

4. METHODOLOGY

4.1 Descriptive Statistics of the Variation in Income Distribution

The first step is to construct an income distribution for each state to determine the income trends associated with solar adoption programs each state, while also to serve as the baseline when comparing the effectiveness of each adoption program. The income distribution in each state is illustrated in Figure 2. Based on the income distribution, California and Connecticut show a relatively similar income spread with an average income of $88,810 and $88,245 respectively. Meanwhile, Oregon's distribution has lower average annual income of $71,250. An average income disparity in each state might affect the robustness of each adoption program, particularly TPO, in driving solar penetration at the LMI households.

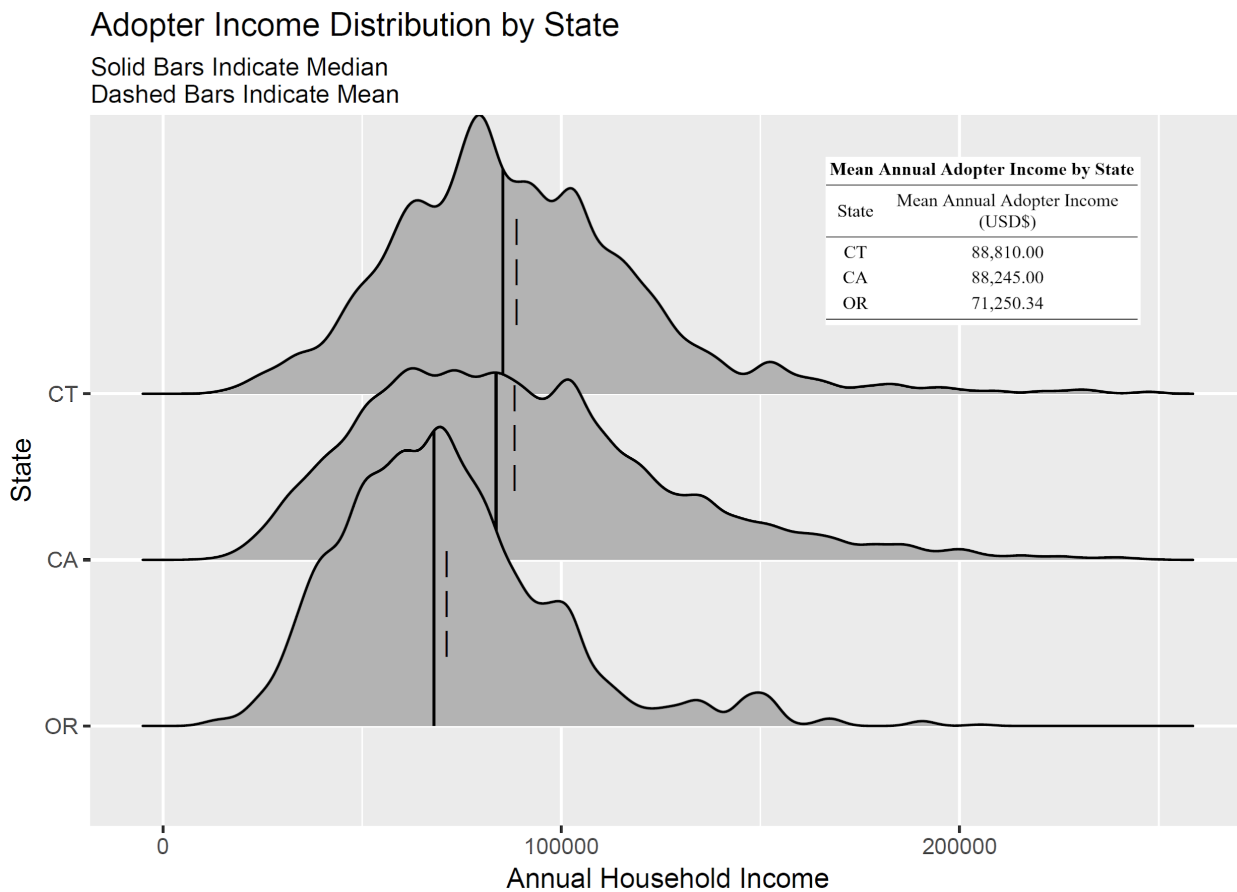

Figure 2: Annual PV Adopter Income Distribution by State

Income Distribution of PV adopters in California

For California, we plot the density of the income distribution for PV adopters with and without the adoption program (TPO and PACE), since there is a wide discrepancy between the frequency of PACE, TPO, and other PV adopters. The distributions is apparent to be normal with a slight skew to the left (lower household income) side. PACE program exceeds other programs in embracing PV adopters from low and moderate income household with the lowest the median household income. Comparing the mean household income of PACE adopters against the broader population in California, there is a large shift in from $88,245 to $77,989, or more than 10% mean income reduction.

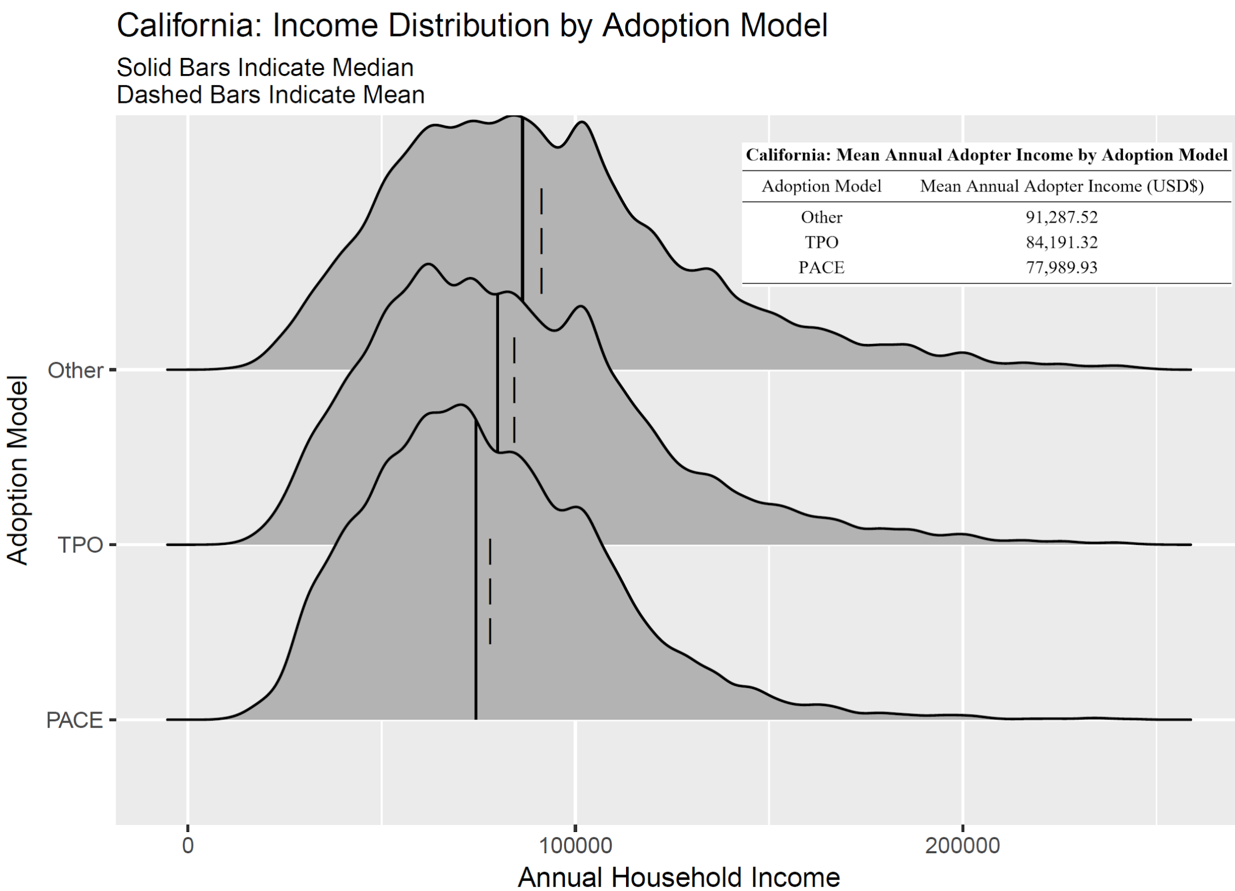

Figure 3: Annual Income Distribution of PV Adopters in California

Looking closely at the density of PV adoption in correlation with the income distribution across the counties in California, it seems that PACE gains more popularity in the county where PACE is less significant. Interestingly, most of counties with high PACE adopters have a lower median household income than TPO-dominating counties. This indicates that PACE might be found to be a more attractive option for less affluent market compared to the TPO option. The regression analysis will provide a quantitative measure of PACE influence in resulting a lower mean income compared to other PV adopters, including those with the TPO financing option.

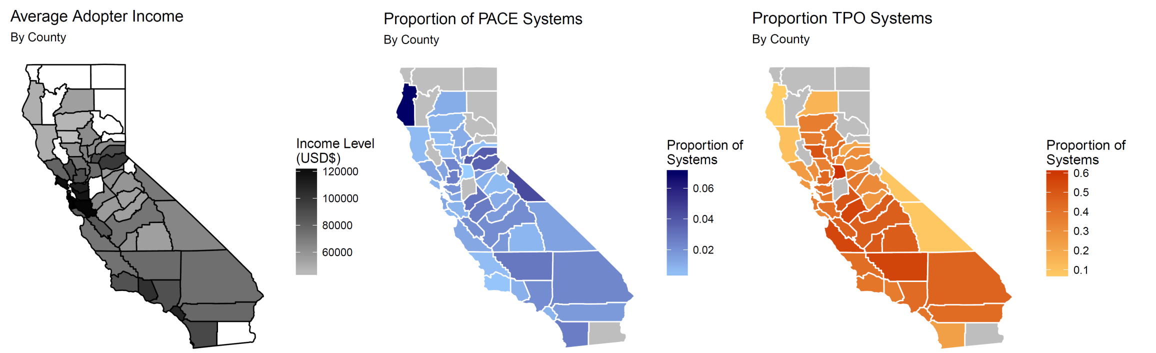

Figure 4: PACE and TPO distributions in correlation to the average household income

<u>Income Distribution of PV adopters in Connecticut</u>

Since our preliminary observation shows some overlap between TPO and Solarize participants, we also include Solarize and TPO interaction in plotting the density of the income distribution, which is normal for all PV adoption programs. In contrast with our hypothesis, Solarize possesses the highest median household income amongst PV adopters in Connecticut, whereas TPO has the lowest. PV adopters within the Solarize even has much higher mean household income than ones without affiliation to any solar adoption program. TPO seemingly lowers the mean income household in Solarize, shown by slightly less mean income value in the Solarize participants with TPO financing (Solarize-TPO interaction).

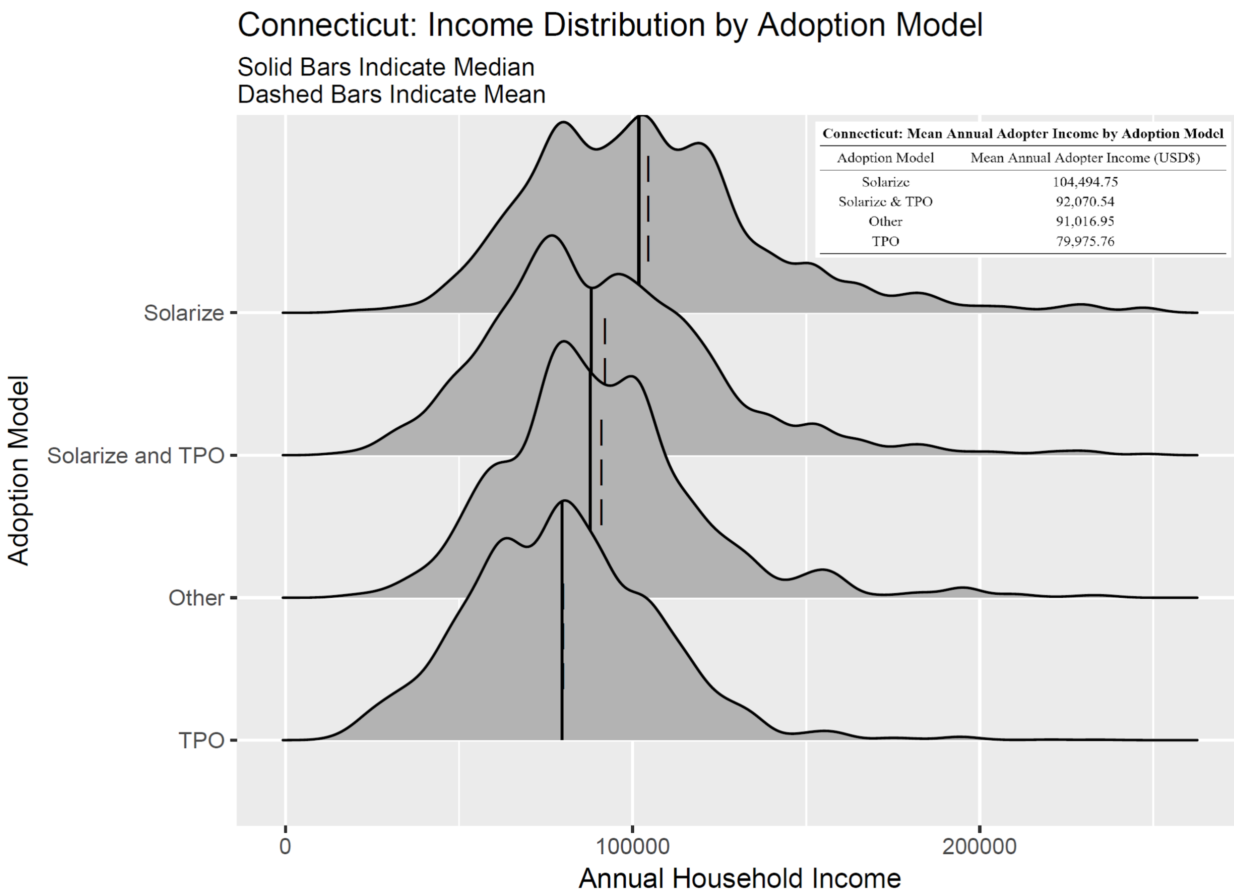

Figure 5: Annual Income Distribution of PV Adopters in Connecticut

We look further to the income distribution for each Solarize campaign to see if any of the campaign characteristics influencing the median household income to be higher in the Solarize participants. The resulting income distributions for each Solarize campaign are inconclusive, especially with the mean income highly varies from one campaign to another. With such an inconsistency of mean household income within Solarize campaign, the regression analysis might provide more in-depth analysis to explain such discrepancy in Connecticut's PV adopters.

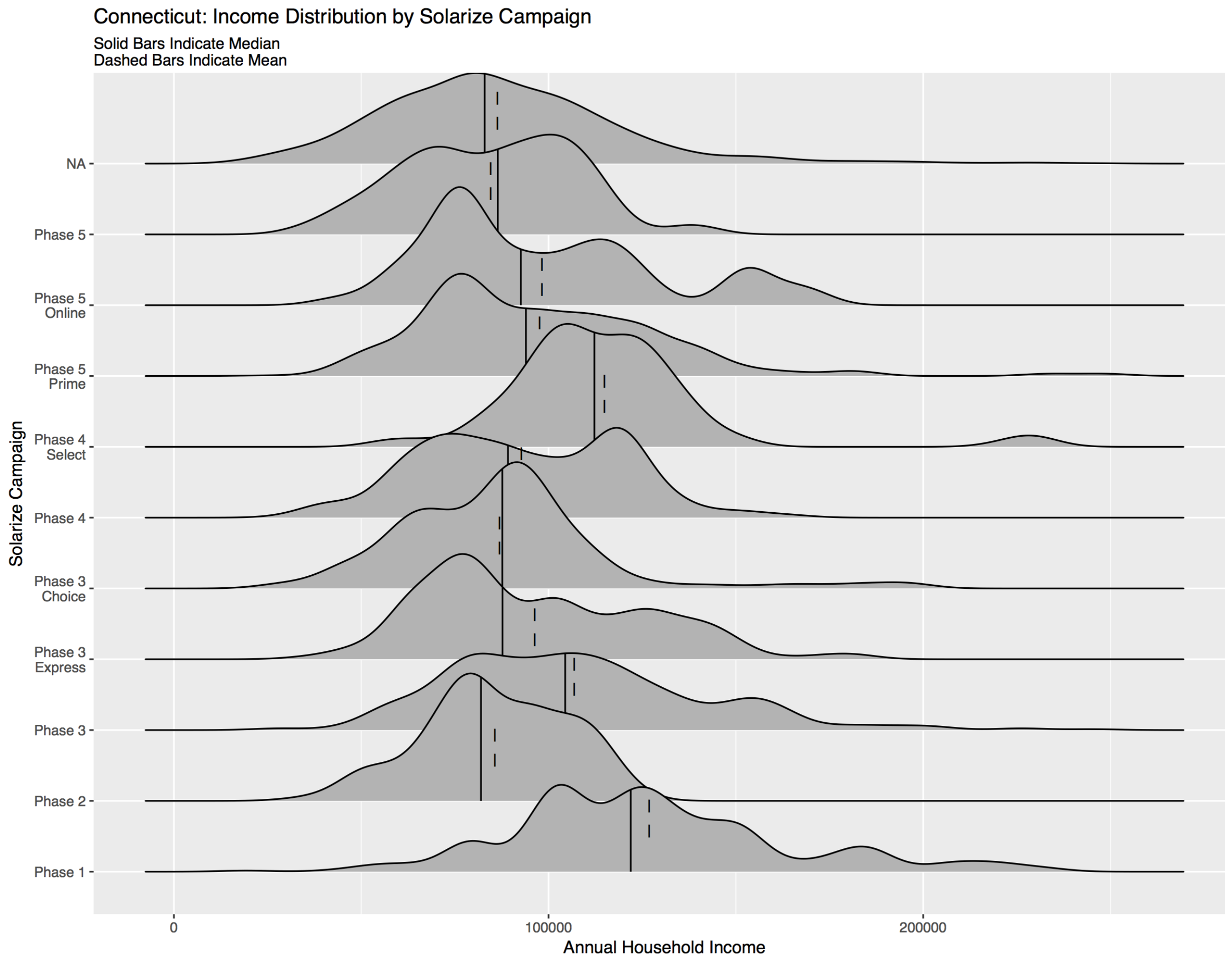

Figure 6: Annual Income Distribution of PV Adopters for each Solarize campaign

<u>Income Distribution of PV adopters in Oregon</u>

The income distributions for PV adopters in each adoption program are shown to be normal with mean values close from one program to another. Similar to Connecticut income distribution, Solarize once again produces the highest mean household income amongst other PV adopters in Oregon. However, TPO has more rigorous effect in lowering the mean income to be at the lowest when combined with Solarize. Since the Solarize campaign information for Oregon is not available, we could not look closely to the income distribution of Oregon's campaign and determine which campaign and/or campaign characteristics influencing Solarize to be preferred by higher income households.

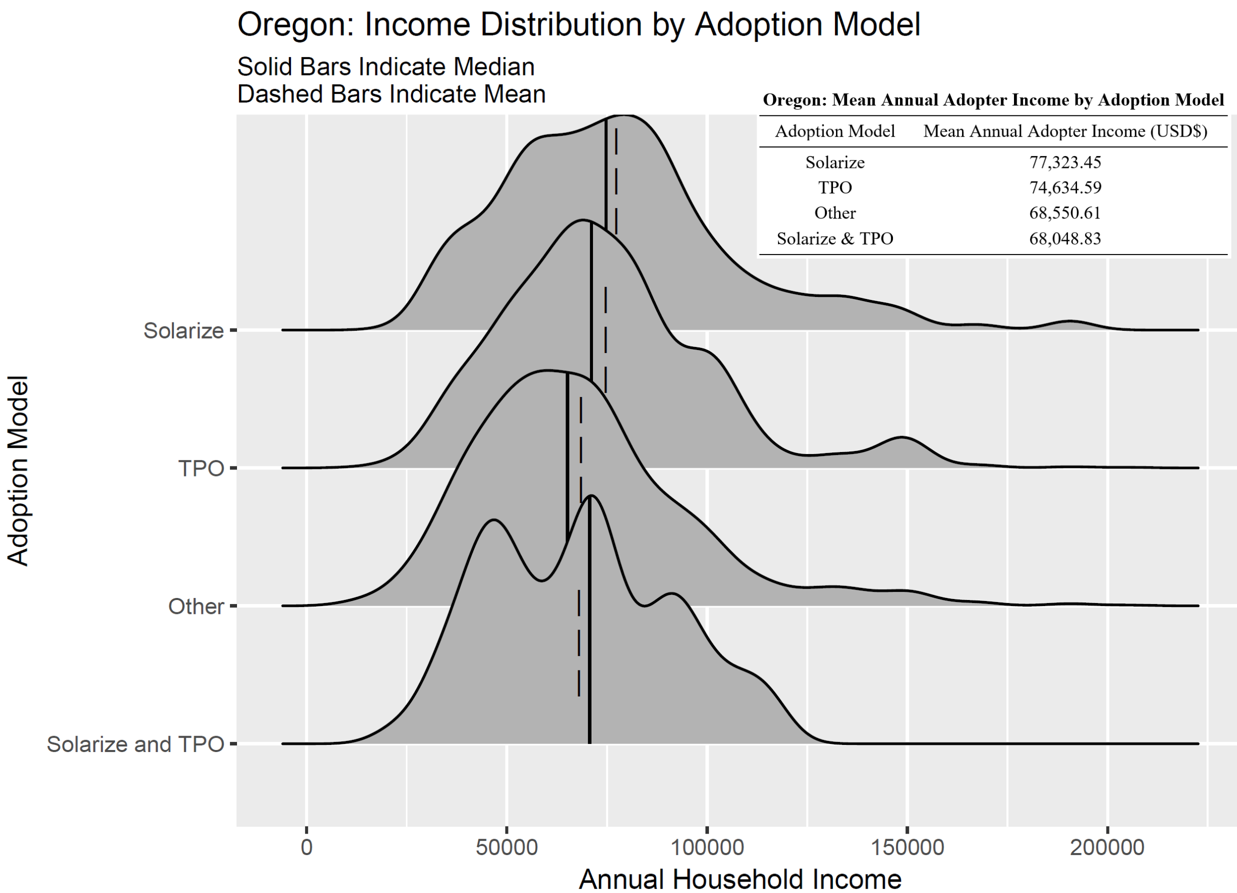

Figure 7: Annual Income Distribution of PV Adopters in Oregon

4.2 Estimation Evidence with Regression Analysis

Our estimation approach aims to provide quantitative evidence of the effect of individual adoption models on the average income of solar PV customers. We regress median annual PV adopter income on several covariates that indicate which adoption model the observation belongs to while controlling for county and time. The regression is run separately for each state and an extra variable is added to the base model to for Connecticut to differentiate between Solarize campaigns. The base model is as follows:

$$income = \beta_0 + \beta_1 PACE_i + \beta_2 Solarize_i + \beta_3 TPO_i + \beta_4 SS_i + \alpha_i + \varepsilon_i \qquad (1)$$

Here $PACE_i$, TPO_i, and $Solarize_i$ are binary indicator variables. SS_i is a continuous variable for system size defined as kW nameplate capacity. We experimented with capturing sources of exogenous variation using different fixed effects (α) including state, county, year, quarter, and month fixed effects. By including a fixed effect, our model controls for variation in income that can be attributed to differences in locality or any unobserved time-varying factors (Gillingham et al., 2016). The county-quarter fixed effect yielded the strongest model and we include this in every regression run. Our model does not differentiate the proportion of solar customers that belong to low and moderate income households. The outcome coefficients, instead, represent a directional change in the average income of solar PV adopters in the adoption program compared to non-program PV adopters. The dependent variable, *$Income_i$*, serves as a proxy to understand how effective each adoption program is at attracting LMI households.

We create several variations of the base model based on the state-specific variables. For example, we modify the base model by removing the PACE components from the model for the Oregon and Connecticut estimation models, while the Solarize components were removed from the California estimation model. We also introduce the LMI-incentives variables to the model, such as PosiGen variable to Connecticut model and Grid Alternatives (GA) variable to the California model, in order to control the LMI effect in those markets. In addition, we introduce the interaction between TPO and Solarize, as well as LMI-installers and Solarize to refine our estimation. For Connecticut, we also add the solarize campaign variable to evaluate the Solarize program characteristics further that might hold some explanatory powers in explaining the potential shift in the median income between the Solarize adopters and the non-Solarize PV adopters. The resulting estimation models for California, Connecticut, and Oregon are shown in Equation (2), (3), and (4) respectively.

$$income = \beta_0 + \beta_1 PACE_i + \beta_2 TPO_i + \beta_3 SS_i + \beta_4 GA_i + \alpha_i + \varepsilon_i \qquad (2)$$

$$income = \beta_0 + \beta_1 Solarize_i + \beta_2 TPO_i + \beta_3 SS_i + \beta_4 Solarize * TPO_i + \beta_5 Posigen_i + \beta_6 Solarize * Posigen_i + \beta_7 Campaign_i + \alpha_i + \varepsilon_i$$

(3)

$$income = \beta_0 + \beta_1 Solarize_i + \beta_2 TPO_i + \beta_3 SS_i + \alpha_i + \varepsilon_i \qquad (4)$$

5. RESULTS AND DISCUSSION

California

Table 3: Estimation model results for PV systems in California

California Model

	Dependent variable:	
	Estimated Average Adopter Annual Income (USD)	
	Base	Grid Alternatives
	(1)	(2)
PACE	-7,912.418***	-8,310.495***
	(327.626)	(326.151)
TPO	-5,458.958***	-5,887.691***
	(97.885)	(97.613)
System Size (kW)	1,997.179***	1,904.318***
	(15.905)	(15.884)
Grid Alternatives		-31,250.580***
		(434.092)
Constant	114,886.500***	115,277.000***
	(2,731.531)	(2,718.850)
Observations	555,684	555,684
R^2	0.267	0.274
Adjusted R^2	0.265	0.272
Residual Std. Error	32,079.060 (df = 553967)	31,930.080 (df = 553966)
F Statistic	117.607*** (df = 1716; 553967)	121.657*** (df = 1717; 553966)
Note:		*p<0.1; **p<0.05; ***p<0.01

The overall California model shows a statistical significant output, yet at high variation with adjusted R2 of 0.265. PACE and TPO have statistically significant influence in increasing the likelihood of capturing the LMI adopters, which were show by negative correlation with the median household income of PV adopters. Meanwhile, system size shows positive correlation with the median income, which is consistent with our hypothesis. Lower income households tend to have lower value of home, such that the PV system size is often restricted to certain size. However, as the continuous variable, system size has less effect in influencing LMI adoption compared to the binary variables as PACE and TPO. On the other hand, the Grid Alternatives coefficient predictably captures the LMI market segment extremely effectively with a highly negative value of approximately 31,000 dollars.

This supports the logic of model, since Grid Alternatives specifically serves adopters with lower incomes. Nonetheless, it is still important to acknowledge that specific incentives for suppliers who carve-out service for LMI adopters may be very influential.

Connecticut

The Connecticut estimation method supports the anomaly in the Solarize income distribution. Solarize is once again associated with the statistically significant increase in the median income of the PV adopters, while TPO does otherwise. The overall model shows statistical significance with adjusted R2 of 0.223, and improved when solarize campaign and Posigen variables are introduced into the model. While Posigen variable and Posigen-Solarize interaction shows similar effect to Grid Alternatives in attracting lower income PV adopters, Posigen is not crucial enough to influence other variables. With only about 50 systems that categorized under posigen, Posigen does not seem to have a neither a statistically significant nor enough explanatory power to influence PV penetration at low to moderate income adopters.

Looking closely to coefficients of each solarize campaign, we could not find any trends and patterns amongst Solarize campaign, even similarly-structured campaign varies in direction and magnitude. It shows that the campaign characteristics, such as length of campaign, town motivation, pricing mechanism, and the number of installers, do not have significant influence in driving Solarize to approach PV adopters at certain income level. Perhaps further study in evaluating each municipals characteristics, along with more social/ qualitative campaign characteristics, such as the role of peer effect and Solarize ambassador, might help explaining a diverse variation in Solarize campaign, as well as an inclination towards higher income adopters.

Table 4: Estimation model results for PV systems in Connecticut

Connecticut Model

	Dependent variable:				
	Estimated Average Adopter Annual Income (USD)				
	Base	Interaction	Posigen	Interaction	Campaign
	(1)	(2)	(3)	(4)	(5)
Solarize	10,312.720***	9,818.923***	9,869.313***	9,877.286***	
	(447.547)	(810.596)	(807.981)	(807.549)	
TPO	-8,796.318***	-9,148.805***	-8,894.790***	-9,029.541***	-7,910.585***
	(518.265)	(708.062)	(706.150)	(706.400)	(923.453)
System Size (kW)	1,743.336***	1,744.058***	1,707.031***	1,706.768***	1,891.201***
	(73.591)	(73.599)	(73.439)	(73.399)	(139.477)
Posigen			-19,073.000***	-12,491.060***	-24,638.490***
			(1,748.511)	(2,274.118)	(2,919.176)
Phase 1					16,903.750***
					(2,932.540)
Phase 2					-18,527.240***
					(3,003.222)
Phase 3					-1,635.416
					(2,052.506)
Phase 3 Express					676.487
					(2,677.120)
Phase 3 Choice					-13,395.230***
					(2,157.556)
Phase 4					-5,179.086***
					(1,547.629)
Phase 4 Select					15,778.780***
					(2,580.162)
Phase 5 Prime					12,948.000***
					(1,540.952)
Phase 5 Online					9,526.113***
					(2,110.799)
Phase 5					-10,436.480***
					(1,703.430)
Solarize*TPO		697.678	731.703	1,081.477	
		(954.890)	(951.799)	(954.426)	
Solarize*Posigen				-15,766.440***	
				(3,485.801)	
Constant	160,834.600***	161,215.100***	161,357.500***	161,352.600***	144,716.300***
	(9,423.651)	(9,438.153)	(9,407.565)	(9,402.514)	(17,062.010)
Observations	18,401	18,401	18,401	18,401	6,055
R^2	0.223	0.223	0.228	0.229	0.259
Adjusted R^2	0.210	0.210	0.215	0.216	0.238
Residual Std. Error	28,231.240 (df = 18110)	28,231.610 (df = 18109)	28,140.080 (df = 18108)	28,124.980 (df = 18107)	29,516.510 (df = 5885)
F Statistic	17.903*** (df = 290; 18110)	17.843*** (df = 291; 18109)	18.305*** (df = 292; 18108)	18.332*** (df = 293; 18107)	12.173*** (df = 169; 5885)
Note:					*p<0.1; >**p<0.05; >***p<0.01

Oregon

Table 5: Estimation model results for PV systems in Oregon

Oregon Base Model

	Dependent variable:
	Blockgroup Median Income
Solarize	-1,897.409
	(1,280.963)
TPO	-2,012.955***
	(723.710)
System Size (kW)	692.773***
	(128.762)
Constant	60,223.280***
	(10,218.950)
Observations	9,351
R^2	0.194
Adjusted R^2	0.154
Residual Std. Error	25,019.630 (df = 8907)
F Statistic	4.846*** (df = 443; 8907)
Note:	*p<0.1; **p<0.05; ***p<0.01

Based on the Oregon regression model, TPO are associated with a statistically significant decrease in estimating the median income of PV adopters. Meanwhile, Solarize, although showing a propensity to lower median income of PV adopters, does not demonstrate statistical significance in the model, such that did not possess any explanatory power and could not be pursued further in this analysis.

6. CONCLUSION AND FUTURE WORK

The results of this project shows TPO to be consistently effective across all the solar PV markets at reducing the average income of residential adopters, suggesting that leasing and power purchase agreements may continue to be an important option for LMI customers. Interestingly, while the PACE program is not specifically designed with low or moderate-income customers in mind, it proves to be very effective at expanding the market towards lower income populations with a negative coefficient of approximately 8,000 dollars. This is consistent with the role of high upfront costs as a significant barrier for households with low cash flow. Solarize, on the hand, produces mixed results with both positive and negative campaign coefficients. Overall, Solarize seems to be correlated with a statistically significant increase in estimated annual income. TPO did a much better job than Solarize at expanding solar PV to the LMI population in Connecticut. This does not imply that Solarize is ineffective in lower income areas, but rather that the Solarize programs analyzed in this project may have been specifically targeted toward higher income areas, with an *ex ante* expectation of higher chances of success. Further analysis is needed to assess the effectiveness of Solarize programs in reaching lower income markets, all else equal.

An expansion of this research should include the effect of the PACE financier or PACE installer in the model to understand whether larger or smaller providers are extending the market to LMI populations disproportionately. Due to data limitations, this project could not assess the differences between Solarize campaigns in Oregon. Furthermore, the substantial difference between the impact of Phase 1 and Phase 2 of Solarize in CT suggests that there are important design characteristics that our research did not capture. Since Phase 1 and Phase 2 Solarize do not differ in length of offer, number of installers, or pricing mechanism, it is possible that detailed data about marketing strategies or volunteer participation may provide more insightful results. Further efforts are needed to assess the effectiveness of community-specific strategies like Solarize. Lastly, a good addition to this research could include an interaction term for the effect of TPO over time. Residential solar leases have been declining and customer ownership tipped the scale away from third-party ownership at the end of 2016. It would be interesting to model the impact of this decline on annual adopter incomes.

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